Estd. in 2008
बेटी बचाओ, बेटी पढ़ाओ

Jayoti Vidyapeeth Women's University, Jaipur

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DIRECTORATE OF RESEARCH & DEVELOPMENT

SYNOPSIS

FOR

Doctor of Philosophy

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Part A: DETAILS OF THE CANDIDATE:

1.	**Name of the Ph.D. scholar (in Block letters)**	**HEENA**
2.	**Faculty**	
3.	**Name of the Department** (Wherever applicable)	**Computer Science**
4.	**Subject / Specialization**	**CSE**
5.	**Topic (Block letters)**	**Decoding Physiological Signals with Graph Neural Networks**
6.	**Academic Session of admission**	**2024-2027**
7.	**Contact details:** **i. Residential Address** **ii. Email** **iii. Mobile no.**	**H.no 347/129K, New Kartar Nagar, Ludhiana, Punjab** **Aroraheena714@gmail.com** **+91 62841-91756**
8.	**Details of Ph.D. Supervisor** **Name:** **Designation:**	**Dr. RAJ SINHA** **Assistant Professor**
	Details of Ph.D. Co-Supervisor/Guide (If any) Name: **Designation:**	**Dr. RAJ SINHA** **Assistant Professor**

Part B: **PROFORMA FOR SYNOPSIS:**

1. Introduction: Given purpose of Research
2. Research Aims and Objectives
3. Review of Literature
4. Research Methodology & Materials
5. Ethical considerations (wherever applicable)
6. Expected outcome of the proposed work
7. References in standard format

Rajsinha

Signature of the Supervisor/Guide

(Seal of the Supervisor with University Name)

Heena

Signature of the Candidate

Heena

Part C: MANUAL FOR PREPARATION OF Ph.D. SYNOPSIS
(Prescribed Format and Specification)

1. GENERAL:

The synopsis is to be considered as a detailed summary of the work with important results highlighting the original contributions in the thesis to be submitted. It should be prepared as per the Research of the Year (RAY) of the University. It should give an outline of the thesis. The review of earlier work is to be minimized with just enough to highlight the contributions in the research work to be reported in the thesis. It is expected that at the time of submission of the synopsis no work is yet to be completed except writing the thesis and all other academic requirements such as course work, comprehensive examinations and the suggestions and directions given by members of the Research Advisory Committee and UREC have been fulfilled.

The Scholar shall give a presentation on his/her proposed research work before the Research Advisory Committee and an expert panel on a date and time notified by the Directorate of Research and Development (DRD).

2. NUMBER OF COPIES TO BE SUBMITTED:

Five hard copies and one soft copy (pdf file) are to be submitted to the University.

3. SIZE OF SYNOPSIS:

The Cover Page & Title Page shall be covered with a transparent sheet. The Cover Page & Title Page should be on a A4 size (200-300 GSM) white paper. While, the size of synopsis should be 10-25 pages of 1 ½ spacing on A4 size (100-120 GSM) white paper.

4. LAY OUT OF SYNOPSIS:

i. **Cover Page & Title page**: A title page of the synopsis should include title of the Research Project, name of the student (with qualifications), name of the supervisor (Annexure – A)

ii. **Declaration**: (Annexure – B)

iii. **Table of Contents**

iv. **Body of the Synopsis**

- **Introduction:** It should provide a brief description to introduce the area of the proposal research work.

- **Research Aims and Objectives**: Broad objectives as visualized to be achieved should be clearly outlined and these should be itemized. These objectives will indicate the major aspects of the study to be undertaken.

- **Review of Literature:** A review of the relevant literature showing the work done previously in the area of proposed research is essential to plan further research effectively. The information given in the review should be supported by references.

- **Research Methodology & Materials:** A plan of work describing the various aspects of the study in a logical sequence along with the methodology to be employed, are the most important aspects of any research plan. Sufficient details to demonstrate that the researcher has a fairly good idea about the nature of work likely to be involved should be provided. In the case of experimental sciences, e.g., which equipment and experimental procedures will be used to obtain the results; in the case of social sciences what resource materials will be used; whether the required information will be obtained from primary or secondary sources, etc. A time schedule for the various aspects of the proposed research may be provided wherever possible.

- Ethical considerations: Does the study require any investigations/interventions to be conducted on the human subjects/patients? (Yes / No). (If applicable enclose the patient consent form and concerned approval; refer Drugs Controller General of India (DCGI) guidelines on www.ctri.in). Does the project involve any drug trials on animals? Yes / No. If so, whether the required and approved facility is available in the animal house? For Questionnaire study (Yes / No) (Questionnaire copy enclosed). Has Institutional ethical clearance been obtained? (Yes / No). Mention Research Advisory Committee approval reference number:

- **Conclusion:** It is important to provide justification for undertaking the proposed research, perhaps in the light of previous work done. It should be possible in most cases to anticipate the specific and general benefits likely to be achieved as a result of the completion of the proposed research.

v. **List of References** (pointed references only in the body): Mention relevant references in Vancouver style, in the order of its appearance in the text. Number each reference consecutively throughout the text. Provide it as a superscript when using as a cited reference. Do not use abstracts as the source of texts; Full text articles should be consulted.

vi. **Gantt chart submitted:** Gantt chart submitted (Yes / No), time required for every stage of thesis work completion is to be specified in detail. Starting from synopsis writing to data collection, processing, analyzing and up to actual writing of thesis.

vii. Research Advisory Committee (RAC) / UREC (As applicable) Approval certificate.

viii. **Annexure C**

ix. **Annexure D**

x. **Annexure E**

5. TYPING INSTRUCTIONS:

6.

- The synopsis should have the following page margins:

Top edge	:	25 to 30 mm
Bottom edge	:	25 to 30 mm
Left side	:	35 to 40 mm
Right side	:	20 to 25 mm

- Tables and figures should conform to the margin specifications. Large size figures should be photographically or otherwise reduced to the appropriate size before insertion.
- The general text shall be typed in Font Style “Times New Roman” and Font Size 12.

- General formatting can be similar to that of the thesis (see format for Ph. D thesis). However, figures and equations are to number using running numbers. References can be numbered as 1, 2, 3, etc., in the order in which they are referred to in the body of the synopsis. Only those which are cited in the synopsis need be given in the list of references.
- **Cover Page & Title Page:** A specimen copy of the Cover page & Title page for synopsis is given in Annexure A.
- **Declaration:** A specimen copy of the Declaration is given in **Annexure B**.
- **Table of Contents:** The table of contents should list all material following it (divisions and subdivisions of body of the synopsis).

7. Binding Specifications:

Each of the five copies of the synopsis should be spiral bound. The cover should be printed in black letters and the text for printing should be identical to what has been prescribed for the title page**.**

8. Submission of Synopsis:

- Five hard copies of the synopsis are to be submitted along with a soft copy of the synopsis (PDF file).

Part D: **SYNOPSIS VERIFICATION:**

1.	**Name & Signature of Scholar: HEENA** Heena
2.	**2.** **a) Remarks:** **Name & Signature of Supervisor/Guide:** **2.** **b) Remarks:** **Name & Signature of Co-Supervisor/Co-Guide: (if any)** Rajsinha Dr. Raj Sinha, Assistant Professor, Faculty of IT & CS, Parul Institute of Engineering and Technology, Vadodara, Gujarat, rajsinha2310@gmail.com
3.	**Remarks:** **Name & Signature of Head of Department:** (wherever applicable)
4.	**Name & Signature of Dean/Director of Faculty:**
5.	**Name & Signature of Director, DRD:**

ANNEXURE – A

Decoding Physiological Signals with Graph Neural Networks

Submitted by

HEENA

Under the Guidance of

Dr. RAJ SINHA
Assistant Professor, Faculty of IT & CS,
Parul Institute of Engineering and Technology, Vadodara, Gujarat

In Partial Fulfillment of the Requirements

for the Award of Degree of

DOCTOR OF PHILOSOPHY

Estd. in 2008
बेटी बचाओ, बेटी पढ़ाओ

Jayoti Vidyapeeth Women's University, Jaipur

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ANNEXURE – B

DECLARATION

I. I, HEENA hereby declare that all the statement made in this application are true, complete and correct to the best of my knowledge and belief and in the event of any information being found false or incorrect or any ineligibility being detected before or after the registration for Ph.D. My candidature is liable to be cancelled, and legal action may be initiated against me.

II. I have deposited the required fee, as notified by the University regularly.

III. I have noted that if my application is found incomplete / defective, the same is liable to be rejected summarily and no correspondence will be entertained in this regard.

IV. I have read and agree with the University Revised Ph.D. Ordinance No. 14 and UGC Regulation – 2009, and all the Amened Regulations or newly passed Regulations by the UGC on or before below mentioned date.

Heena

Place: Jaipur

Date: 11/03/2025

(Signature of the Applicant)

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ABSTRACT

This study proposes a Multi-Modal Graph Neural Network (GNN) framework, which decodes physiological signals from multiple sensor modalities-cum-types, such as ECG (cardiac activity), EEG (brain activity), and EMG (muscle activity). The main challenge is in the proper analysis of high-dimensional noisy and time-dependent data while maintaining spatial, temporal, and inter-modal relationships. Current physiological signal decoding methods fail to address such complexities because this real-world application has been largely neglected in healthcare, sports science, and rehabilitation. The proposed framework constructs a unified graph representation where each physiological signal is modelled as a node with embedded temporal and spatial dependencies. Graph-based preprocessing techniques are used to address noise, missing data, and sensor variability to ensure robust feature extraction. In addition, dynamic graph models are used to capture evolving signal patterns for the real-time detection of subtle physiological changes. The contributions of this research are expected to be a new multi-modal GNN architecture that will improve interpretability and accuracy for the decoding of physiological signals. Model scalability and generalizability will thus be cross evaluated on various datasets so that this model can be applied to different sensor configurations and population groups. The approach may prove to help in advancing next-generation physiological signal analysis for real-time health monitoring, early anomaly detection, and personalized adaptive therapies.

1. INTRODUCTION

Physiological signal decoding is the process of extracting the electric, chemical, and mechanical activities from the human body and interpreting them. Signals like Electrocardiograms (ECG), Electroencephalograms (EEG), and Electromyograms (EMG) [1] give very clear and good details about how all the different systems are functioning, for example, cardiovascular, nervous, and muscular. These signals carry vital information about the health and performance of the body, and hence, the accurate decoding of them is essential for a wide range of applications. In healthcare, physiological signal decoding plays a central role in diagnosing diseases and monitoring the health of patients; thus, it is used in predicting potential health risks. For example, decoding ECG signals can determine the presence of arrhythmias while EEG signals are pivotal in identifying neurological disorders such as epilepsy.

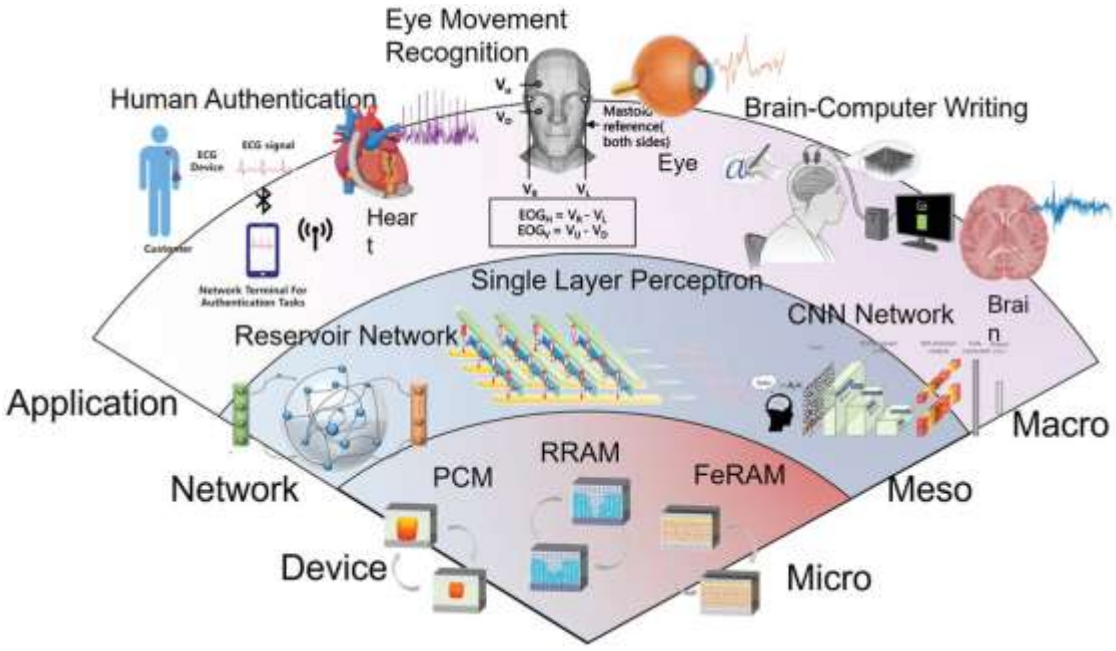

Figure 1. Physiological Signal Concept

Apart from healthcare, physiological signal decoding [2] also has a very important role in sports science. Here, it acts to optimize performance and prevent injury. Athletes, along with trainers, can get information regarding the pattern of muscle activation, fatigue levels, and biomechanical efficiency through EMG signals during training. Likewise, EEG signals may be utilized to assess mental focus and cognitive load so that tailormade strategies for reaching peak performance of athletes can be devised. In rehabilitation also, the task of physiological signal decoding assumes equal importance. Decoding of signals from involved muscles or portions of the brain helps in charting the path of recovery progress, devising individualized rehabilitation plans, and assessing the merit of rehabilitation exercise. For example, EMG data monitoring for muscle activity in the post-operative or stroke state is really crucial information for adapting protocols of rehabilitation exercises.

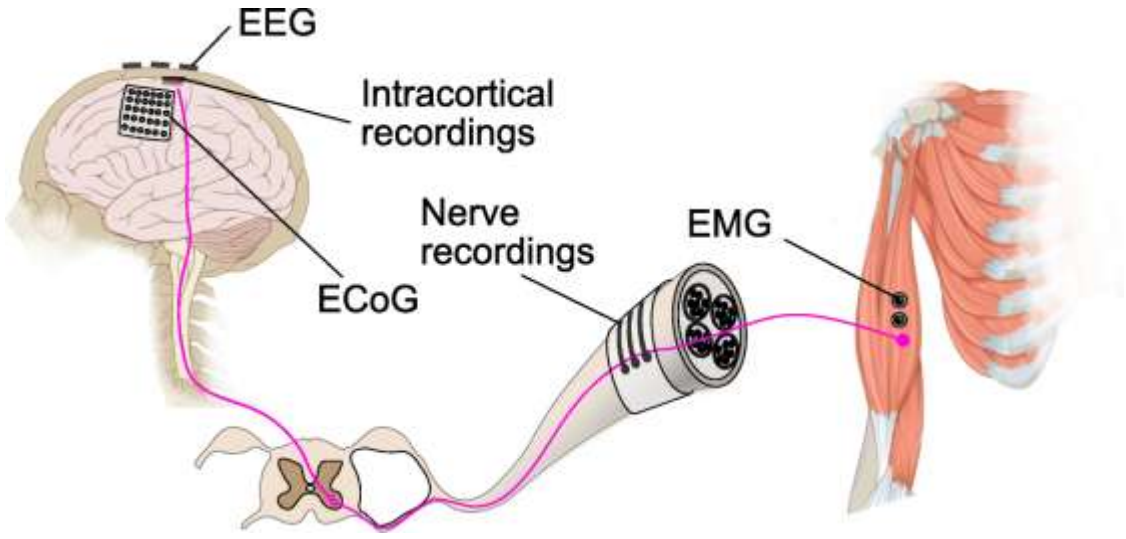

Figure 2. EEG, ECoG, EMG

The fusion of different types of sensor modalities, such as ECG, EEG, and EMG, [3] has revolutionized physiological signal analysis. This offers a more global perception of the state of the body and represents everything in a combined form. Each modality captures different physiological phenomena, and the combination enhances the overall accuracy and depth of analysis. For example, the ECG speaks about the heart's electrical activity, EEG regarding wave patterns of the brain, and EMG relating to muscle activities. Combining data from such modalities gives researchers and clinicians a clue into the complex interdependencies between these physiological systems to make a much more accurate diagnosis and intervention strategy [4].

1.1 Importance of Research

The need for multi-modal sensor analysis [5] is very important in conditions where the interaction of different systems needs to be understood. For instance, in the assessment of stress, ECG can measure heart rate variability, EEG can assess cognitive load, and EMG can detect muscle tension-all combined for a comprehensive profile of the body's response to stress. For rehabilitation of motor disorders, EEG and EMG data fusion help track the relationship between brain signals and muscle responses, thus allowing for targeted therapies. Moreover, multi-modality approaches contribute to the strong signal decoding mechanism because it involves minimal dependency on a single mode, which is always contaminated with noise and artifacts. In multi-sensor methods, data from these sensors is used to minimize such errors or make the system reliable during the process of analysis.

Other applications of multi-modality sensor approaches [6] are being used to improve wearable technologies, IoT-enabled health devices, and so on. Diverse sensors in these devices can facilitate real-time continuous monitoring of multiple physiological parameters and may enable early

anomalies and personalized health management. In sports science, multi-modal systems are now being used for developing smart wearables that will not only monitor physical performance but also analyze the mental and emotional states of an athlete to offer a holistic assessment of their performance. In short, this means multiple modalities of a sensor enhance decoding depth, with increased accuracy concerning actual applications in the sports and healthcare domains, among others.

1.2 Significance of the Research

This piece of research develops novel innovations at the decode the physiological signal while merging the integration of GNNs during mult-modal analysis[6]: signals related to ECG, EEG, or EMG signals. Due to signal interdependency, noisy properties, or overall signal complexities which conventionally inhibit traditional techniques by the failure machine learning based strategies. The GNNs will enhance the real-time monitoring, diagnosis, and decision-making process in healthcare, sports science, and rehabilitation. It catches such complex conditions like cardiac arrhythmias and neurological disorders with better view while information regarding brain-muscle interaction is provided to facilitate personal rehabilitation. It improves multi-modal physiological analysis in sports science for the optimization of a training regimen, injury prevention, and workload management [7].

This study further contributes to AI by revealing how GNNs [8] can be applied to model complex physiological data effectively, furthering wearable technology, IoT-enabled healthcare, and real-time monitoring systems. The work opens a door to much more accurate, scalable, and robust physiological signal decoding that connects AI with human physiology [9].

1.3 Research Questions

1. How can Graph Neural Networks be employed to efficiently decode multi-modal physiological signals?
2. Why is spatial, temporal, as well as inter-modal relation essential in the analysis of physiological data?
3. How would GNN help in coping up with issues posed by realistic physiological signals like noisy, incomplete and variable nature of signals?
4. What is the benefit of the proposed multi-modal GNN architecture when compared with typical machine learning model for the medical decision making as well as the rehabilitation application?
5. How does this advance the cause of real-time health monitoring, early anomaly detection, and adaptive therapies?
6. How scalable is the proposed model for various datasets, sensor configurations, and population groups?

2. RESEARCH AIMS AND OBJECTIVES

2.1 Research Aims

The main objective of the research is to design and test a new multi-modal graph neural architecture to decode physiological signals, thus allowing for an accurate and robust analysis of complex, high-dimensional data from various sensor modalities. A state-of-the-art method in processing physiological signal methodologies by harnessing the specific capabilities of Graph Neural Networks (GNNs) [12] that are tailored for modelling spatial, temporal, and inter-modal relationships existing in the signal. This approach will fill in the gaps of the current decoding techniques and pave the way for the next generation of applications in healthcare, sports science, and rehabilitation.

The objective is to develop a framework that can combine various sensor modalities such as ECG (cardiac activity), EEG (brain activity), and EMG (muscle activity) into a unified graph representation [13]. This representation will bring out both individual characteristics of each signal and their interactions. The goal of the research was to improve interpretability and accuracy in decoding multi-modal signals, specifically in conditions where interdependencies among physiological systems were critical. Some examples include correlations between EEG and neural activity and movement, used for the prediction of muscle responses via EMG: motor control, rehab progress, or even early signs of neurological disorders.

Another important goal is that noise, missing data, and variability in physiological signals can be mitigated. It is noisy and sparse real-world data generated based on artifacts of motion in the body and also environmental interference and sensor failure of wearable or clinical sensors [14]. Such noise in preprocessing should be supported by strong models along with graph-based models bringing out high accuracy in decoding. The gaps and noise effects of data should be reduced since

the research will benefit from how GNNs may represent relationships and propagate information in graph nodes toward filling gaps in data and relating correctly in practical applications.

The further goal the paper has is to incorporate temporal dynamics into the multi-modal GNN framework [15]. Physiological signals are time-dependent, with patterns that evolve over milliseconds to minutes. Therefore, a few approaches in this research further introduced the temporal information into the graph structure, either by embedding time-series features into the nodes of the graph or using dynamic graph models. The expectation from this is the improvement in the system's capability to detect very subtle changes in physiological signals that would be so much needed in real-time health monitoring, early anomaly detection, and adaptive therapies.

The proposed GNN framework also aims at evaluation of its scalability and generalizability since decoding physiological signals typically requires the generalization across various populations, sensor configurations, and environmental conditions [16]. With testing on multiple datasets for the suitability of this study under various use cases and demographics, the study will be designed with extensive development in mind to meet the requirements of developing a very adaptable solution-from individual health tracking through wearable technology to the monitoring of large patients in healthcare systems.

2.2 Research Objectives

The objectives of research are as follows,

1. Conduct a detailed literature review of existing techniques on physiological signal decoding, multi-modal sensor fusion, and Graph Neural Networks.
2. Develop a multi-modal GNN architecture for decoding physiological signals from diverse sensor modalities, such as ECG, EEG, and EMG.
3. To integrate spatial, temporal, and inter-modal relationships into a unified framework for accurate and robust signal decoding.
4. Tackle the problem of noise, missing data, and variability in physiological signals by employing graph-based preprocessing and modeling techniques.
5. To incorporate time dynamics in the decoding of signal for real-time monitoring and for early anomaly detection.
6. To evaluate the scalability, generalizability, and performance of the proposed model across diverse datasets and applications.

3. REVIEW OF LITERATURE

Recently, ECG classification techniques have advanced into new graph-based and neural network approaches, which yield improved accuracy, efficiency, and robustness.

In recent studies, **Qiang, Y., et al. (2024) [17]** proposed a model called Conv-RGNN, which involves a graph structure for the efficient capturing of spatial relationships among the 12-lead ECG signals. Their model has been superior in terms of efficiency, speed, and robustness across a variety of datasets, making it a highly efficient solution for the analysis of ECG.

Duong, L. T., et al. (2023) [18] trained a Graph Neural Network (GNN) on large-scale ECG datasets, achieving human-level diagnostic accuracy of up to 100%. Their approach not only outperformed state-of-the-art models but also proved to be highly effective for real-time diagnosis, underscoring its potential for clinical applications.

Zeinalipour, K., and Gori, M. (2023) [19] proposed three graph-based approaches for ECG classification. The best accuracy obtained by these models was 99.38% on the PTB Diagnostics dataset, which indicates their precision and effectiveness in detecting cardiac conditions.

Ruan, H., et al. (2022) [20] have proposed a multi-domain approach for arrhythmia detection based on analyzing ECG signals in the spatial, spectral, and temporal domains using self-attention mechanisms. This method improved the accuracy of detection by extracting information from cross-dimensional views of the ECG data.

Zhao, X., et al. (2022) [21], developed ECGNN: the model that combines feature extraction with Graph Neural Networks for capturing interlead interrelationships between the 12 ECG leads. It is validated on large-scale datasets to show the model's capability of improving the classification accuracy of ECGs and thus the potential for use cases in large-scale clinical settings.

Mansi, S. A., et al. (2022) [22] This paper is on the promise of personal comfort models (PCMs) for human-centric thermal comfort in buildings. Real-time comfort measurement using physiological data from wearable sensors can revolutionize building design and operation. In this study, 52 participants were exposed to three thermal conditions: cold, warm, and neutral. Physiological signals, including EEG, HRV, EDA, and ST, were recorded non-invasively through wearables during 219 tests. The results indicated that physiological features were significant in distinguishing between cold and warm sensations, whereas neutral sensations were not as distinguishable. Differences ($p < 0.01$) were observed in EEG, HRV, EDA tonic component, and mean ST. These results prove the feasibility of physiological measurements in advanced PCMs, which would help in designing individualized thermal comfort and energy-saving strategies.

Ramadoss, J., et al. (2022) [23] This paper explores brain-heart coupling using fractal theory and sample entropy analysis of EEG and R-R interval signals. Forty-eight subjects performed the NASA Multi-Attribute Task Battery II with different physical activity levels: either stationary bike speed or treadmill speeds. Results include significant correlations between EEG and R-R signal complexities, which validate activation coupling between brain and heart. These findings aid in the evaluation of organ interaction and network physiology.

Vallabhaneni, R. B., et al. (2021) [24] Deep learning is an emerging field in biomedical engineering where decoding of brain activity from EEG data is possible. The paper presents an overview of deep learning algorithms commonly used such as CNNs, autoencoders, and RNNs along with their applications in brain-computer interfaces, cognitive neuroscience, and diagnosing brain disorders. Future research direction sections include parameter selection, computational complexity, and generalization capability.

Thiam, P. et al., (2021) [25] This work bridges the gap in traditional methods for assessing pain by indicating multi-modal deep learning approaches to automatically assess pain intensity from bio-physiological data. State-of-the-art performance was obtained with supervised models; however, a self-supervised approach enhanced data efficiency by generating synthesized physiological data and fine-tuning models trained on smaller datasets. These techniques assist in avoiding certain issues associated with data scarcity and generalization while developing automated pain assessment tools.

Ortega, P., & Faisal, A. A. (2021) [26] Investigates Non-invasive BMIs for decoding hand-specific force control using EEG and fNIRS data. It is found that a deep learning architecture, cinnatt, with attention and residual layers can outperform linear models in fusing EEG and fNIRS with an accuracy to decode bimanual forces. The results found cortical encoding differences between hands and force levels providing improved robustness in BMI robotic devices and insight for motor rehabilitation applications.

Table 1. Literature Review Finding

Author Name (Year)	**Main Concept**	**Findings**	**Limitations**
Qiang, Y., et al. (2024)	Conv-RGNN model for ECG analysis using graph structure.	Demonstrated superior efficiency, speed, and robustness across datasets for spatial relationships among 12-lead ECG signals.	Specific datasets used and scalability to real-world clinical scenarios not discussed.
Duong, L. T., et al. (2023)	Graph Neural Network (GNN) for ECG classification.	Achieved human-level diagnostic accuracy (up to 100%) and real-time diagnosis capability, outperforming state-of-the-art models.	Generalization beyond large-scale datasets and practical implementation challenges in clinical settings unclear.
Zeinalipour, K., and Gori, M. (2023)	Graph-based approaches for ECG classification.	Best accuracy of 99.38% achieved on the PTB Diagnostics dataset, demonstrating precision in detecting cardiac conditions.	Limited validation across diverse datasets and potential overfitting concerns not addressed.

Ruan, H., et al. (2022)	Multi-domain approach for arrhythmia detection using self-attention mechanisms.	Improved arrhythmia detection accuracy by analyzing ECG signals in spatial, spectral, and temporal domains.	Scalability and computational cost of multi-domain analysis not fully explored.
Zhao, X., et al. (2022)	ECGNN model for capturing interlead relationships in 12-lead ECGs using Graph Neural Networks.	Improved classification accuracy validated on large-scale datasets, showcasing potential for clinical applications.	Dependency on large-scale datasets and generalizability for smaller-scale clinical studies remain uncertain.
Mansi, S. A., et al. (2022)	Personal comfort models (PCMs) for thermal comfort in buildings using wearable physiological sensors.	Physiological signals (EEG, HRV, EDA, ST) distinguished cold/warm sensations; findings support energy-saving and individualized thermal comfort.	Neutral thermal sensations were less distinguishable; requires further validation across diverse populations.
Ramadoss, J., et al. (2022)	Brain-heart coupling analyzed via fractal theory and sample entropy.	Significant correlations between EEG and R-R complexities during varying physical activities	Focus limited to controlled experimental settings, lacking

		validated brain-heart activation coupling.	broader application insights.
Vallabhaneni, R. B., et al. (2021)	Deep learning in EEG decoding for biomedical engineering.	Overviewed algorithms (CNNs, RNNs, autoencoders) applied in brain-computer interfaces, neuroscience, and brain disorder diagnosis.	Challenges in parameter selection, computational cost, and generalization highlighted as areas for future research.
Thiam, P., et al. (2021)	Multi-modal deep learning for automated pain intensity assessment.	Supervised and self-supervised models enhanced data efficiency; state-of-the-art performance achieved in pain assessment from physiological data.	Requires large data and faces challenges in generalization due to data scarcity.
Ortega, P., & Faisal, A. A. (2021)	Non-invasive BMIs for decoding hand-specific force using EEG and fNIRS.	Deep-learning architecture (cnnatt) improved bimanual force decoding accuracy and robustness, aiding BMI	Further research needed for real-world applications and avoiding hand cross-talk in complex tasks.

		robotics and motor rehabilitation.	

3.1 Key Findings

1. **GNNs Enhance ECG Signal Classification:** Conv-RGNN (Qiang et al., 2024) and ECGNN (Zhao et al., 2022) are examples of models that capture spatial relationships between 12-lead ECG signals and enhance the accuracy of classification.
2. **High Diagnostic Accuracy with GNNs:** Human-level diagnostic accuracy was achieved in large-scale ECG datasets trained with GNNs (Duong et al., 2023), with up to 100% accuracy, thus establishing their potential for clinical applications.
3. **Multi-Domain Approaches Enhance Detection Accuracy:** Ruan et al. (2022) combined the spatial, spectral, and temporal domains using self-attention mechanisms to improve arrhythmia detection accuracy.
4. **Physiological Data in Real-Time Monitoring:** EEG, HRV, and EDA signals can be used to distinguish between thermal comfort conditions. This can result in personalization of health monitoring as shown by Mansi et al. (2022).
5. **Insights into Brain-Heart Coupling:** It has been demonstrated that the coupling between EEG and heart signals (Ramadoss et al., 2022) validates complex organ interactions and opens new avenues for health diagnostics.
6. **Advancement in Multi-Modal Learning for Biomedical Applications:** Multi-modal fusion, for instance, EEG and fNIRS data (Ortega & Faisal, 2021), improves the performance of brain-machine interfaces with an enhanced robustness for motor rehabilitation applications.

3.2 Research Gaps

1. **Under-investigated, Multi-Modal Physiological Signal Integration in GNNs :** Most research currently focuses on a single-modality ECG-based GNN models, for instance, Conv-RGNN or ECGNN, to carry out cardiac signal analysis. Limited research exists with the integration of multiple physiological signals such as EEG, EMG, and HRV in the unified graph representation. Multi-modal GNN architecture exploration could advance robustness and generalization across a broader application space for health care.
2. **Lack of Proper Noise Handling, Missing Data, and Temporal Dependencies in Physiological Signal Graphs :** Although some research includes spectral, spatial, and temporal domains (e.g., Ruan et al., 2022), there is still a lack of proper handling of real-world noise and missing data in graph-based physiological models. Probably better model robustness can be gained through adaptive techniques such as graph imputation, self-supervised learning, and hybrid attention mechanisms.
3. **Lack of real-time multi-lead ECG processing and edge deployment :** Although ECG-based GNNs have recently attained accuracy into very high ranges (for example, Duong et al. 2023), real-time implementation and edge computing applications have not been probed deeply into. Effective graph processing methods should be created for wearable devices to support the real-time monitoring and early health anomaly detection process.
4. **Limited Exploration of Cross-Organ Interaction and Network Physiology in GNNs:** Brain-heart coupling and physiological interactions have been so far mostly explored with traditional fractal theory or entropy analysis, such as in Ramadoss et al., 2022. This paper focuses on applying GNN-based frameworks to model organ-to-organ connectivity in

order to enhance the predictive diagnostics of complex physiological conditions, for instance, relationships between EEG and ECG.

5. **Data scarcity and the need for self-supervised learning in multi-modal physiological graphs:** Although Thiam et al. (2021) took the lead in self-supervised learning for pain, similar methods haven't been mainstreamed in physiological GNN research so far. Generative approaches addressing data scarcity (e.g., GAN for synthetic physiological signals) could improve model training and generalization in low-data scenarios.

4. RESEARCH METHODOLOGY

The proposed research methodology to achieve the identified objectives of the paper on "Multi-Modal Graph Neural Architectures for Next-Gen Physiological Signal Decoding" was derived from the above point of view. In this, systematic stages shall consist of literature review, data collection, design, implementation, testing, and evaluation and validation stages. The steps are as below:

4.1. Literature Review

The study begins with an extensive literature survey to outline present trends, problems, and shortcomings in the topics of physiological signal decoding, multi-modal sensor fusion, and GNNs [27].

- Discuss earlier studies on the decoding of physiological signals like ECG, EEG, and EMG.
- Discuss methodologies for integrating multivariate data or handling noise and missing data in physiological signals.
- Analyze the use of GNNs and other advanced deep learning architectures for multi-modal signal processing.
- Benchmark datasets and metrics of evaluation of similar research papers

4.2. Data Collection and Preprocessing

- **Available Dataset:** Pick any public dataset containing multi-modal physiological signals including ECG, EEG, EMG. Example datasets may consist of health monitoring systems, datasets of stress-related detection, or datasets of the study of rehabilitation.
- **Data Preprocessing:** Noise reduction and signal normalization eliminate missing or incomplete entries from the data. Cleaning the signals is further done by making use of different techniques like the application of the bandpass filtering or artifact removal [28].
- **Data Annotation:** Datasets must be very well annotated. Labels should give a representation for the condition or activity observed: level of stress, condition of the cardiac, or movements of the motor, among others.

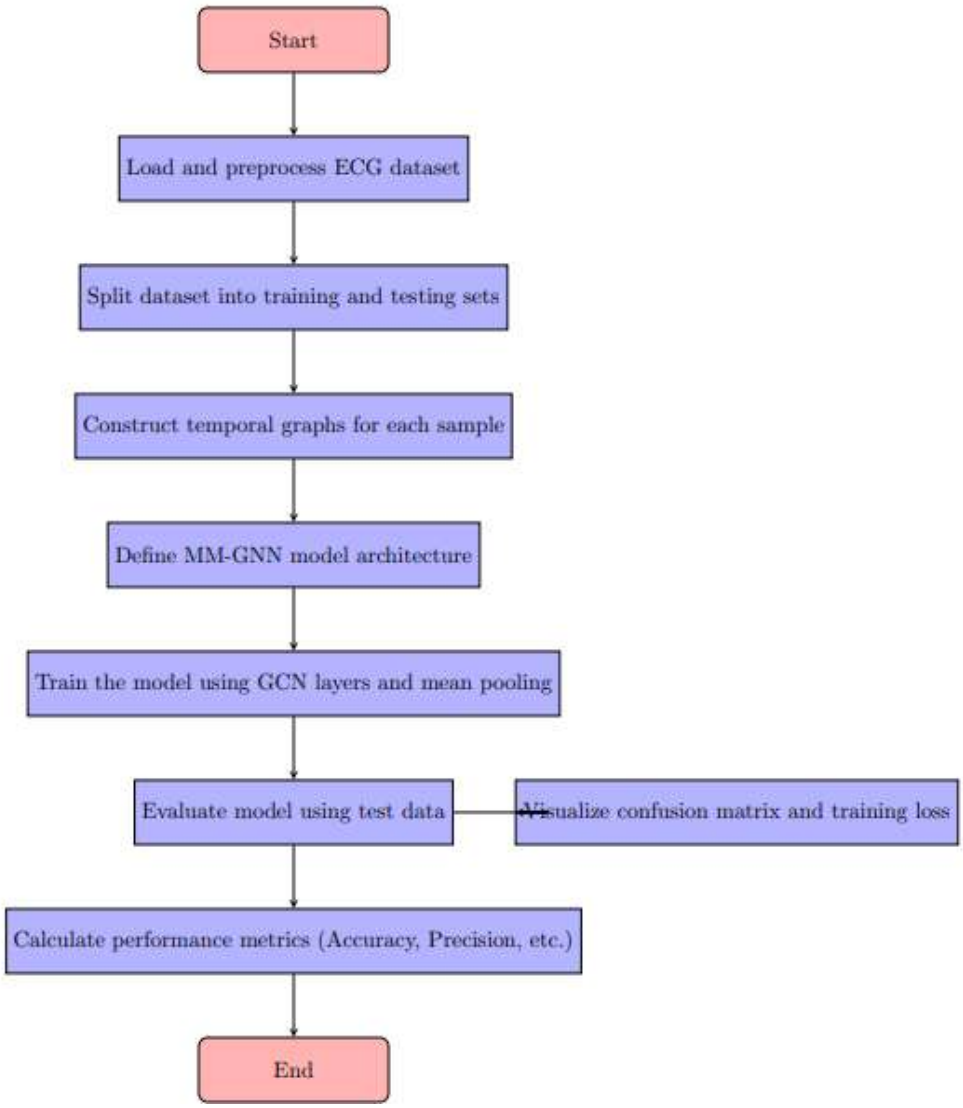
Start
Load and preprocess ECG dataset
Split dataset into training and testing sets
Construct temporal graphs for each sample
Define MM-GNN model architecture
Train the model using GCN layers and mean pooling
Evaluate model using test data
Visualize confusion matrix and training loss
Calculate performance metrics (Accuracy, Precision, etc.)
End

Figure 3. Research Flowgraph

4.3. Graph-Based Model Design

Graph Construction: Develop an approach to describe the multimodal physiological signals in graph format. Nodes can be generated based on sensor modalities including ECG, EEG, EMG and interaction or the relationship between these is described as their edges.

Feature Engineering: Learn frequency, amplitude, and time domain pattern features of every modality and then encode it onto nodes within a graph.

Graph Neural Network Architecture: Design the GNN architecture [29] in a way that it can process this graph representation in order to extract spatial as well as temporal dependencies. Its major components will be:

- Spatial feature extraction- Graph Convolutional Networks
- Temporal mechanisms or Graph Recurrent Networks, as well as Graph Attention Mechanism for time series dependencies
- Layers of multi-modal fusion to allow integration and information processing of several sensor modalities

4.4. Implementation and Model Training

- **Framework Selection:** Implement this GNN architecture using deep learning frameworks such as PyTorch Geometric, TensorFlow, or DGL [30].
- **Training Pipeline:** Implement training pipeline with loss function (either cross-entropy or mean squared error) that is accompanied with optimization algorithms: Adam or SGD.
- **Hyperparameter Search:** Try several parameters such as learning rate, graph depth and node features which can optimize your model's performance.
- **Data Augmentation:** Use synthetic data generation or GANs to augment the data and improve the generalization capability of the model.

4.5. Evaluation and Validation

- **Evaluation Metrics:** Accuracy, precision, recall, F1 score, and area under the ROC curve of the proposed model
- **Comparison with Baselines:** The results from the proposed GNN architecture should be compared with results obtained from the traditional ML models such as SVM, k-NN, and other DL models, CNNs, RNNs, etc.
- **Cross-validation:** Execute k-fold cross-validation to determine if the outcome would not over-fit
- **Real World Testing:** Test the model on data from the real world to establish the extent of the solution being workable and sound in the practical sense

4.6. Development Application

Design a proof-of-concept application or prototype framework that integrates the proposed GNN model for real-time physiological signal decoding. The application can target some specific use cases, for example, wearable health monitoring, athlete performance tracking, or rehabilitation systems.

4.7. Documentation and Reporting

- All findings, methods, and results are documented in detail in the research.
- The study's contributions, limitations, and future work areas are summed up.

4.8. Ethical Considerations

The fact that the data to be used in this research are already available raises less concern over the ethical side since it is well prepared for the handling and use of pre-collected data especially sensitive physiological signals such as ECG, EEG, and EMG. Data to be used will have been cleared on ethical approval and anonymized data, where, at some point, personal identifiers would have been removed to ensure privacy.

5. EXPECTED OUTCOMES AND POTENTIAL CONTRIBUTIONS

5.1 Expected Outcomes

The main expectation for this work is that the introduced multi-modal GNN framework makes the decoding precision and robustness significantly better as it relates to the modalities such as ECG, EEG, and EMG. The spatial, temporal, and inter-modal relationships will be used more efficiently to enhance a comprehensive understanding of the complex interactions among these physiological signals, so it is likely to detect slight changes in physiology more effectively than today, such as early manifestations of neurological disorders, cardiac arrhythmias, and musculoskeletal dysfunctions. It is going to overcome a lot of limitations of machine learning techniques for traditional approaches when applied to the real world where data is always noisy, incomplete, and of variable quality. In the model by incorporating dynamics of time, it will respond to real-time changes in the physiological states with a high amount of utility that would be derived from continuous health monitoring, early anomaly detection, and adaptive therapies.
The framework may not behave as expected for all datasets. Variability in sensor configurations, data quality, or population demographics may affect the results. Model generalizability may depend on the complexity of the dataset and the physiological conditions being monitored. Therefore, even though positive results are expected, the findings may vary, and further refinement or model adaptation may be required.

5.2 Potential Contributions

It has great potential applicability toward several fields, mainly health care, sports science, and rehabilitation. This proposed GNN framework may revolutionize the monitoring and diagnosis of complicated medical conditions by healthcare professionals for an accurate and reliable multi-modal physiological signal decoding. Early detection of disorders like cardiac arrhythmias, neurological conditions, and musculoskeletal dysfunctions will allow intervention so that the condition for the improvement of the patient and cost can be minimized.

In the case of precise observation and evaluation of real-time, athletic physiological signals in sports science, this would redefine the idea of performance analytics, where it would enable improving the capacity to prevent overtraining or injury by optimizing the training regimen. With the combination of EEG and EMG signals, coaches and athletes will thus gain a more direct understanding of their mental and physical states while in training or during competition and consequently approach matters towards performance with much more specificity and efficiency.

This can be applied in rehabilitation settings to advance recovery tracking and tailored therapy. The model could assist in the development of adaptive rehabilitation systems, such as intelligent prosthetics and exoskeletons, in deciphering the physiological interaction between different systems such as brain-muscle activity. One day, this will revolutionize the improvement of life for anyone suffering from neurological or musculoskeletal impairment, as they will receive better, more tailored treatment programs. This research contributes to the AI body of work because it can be used in the demonstration of capabilities of GNN in handling complex multi-dimensional data structures. There could be findings that will lead to innovation in the fields of wearable technology, IoT-based health care systems, and in real-time monitoring of physiological conditions.

5.3Limitations

The above proposed multi-modal GNN framework has lots of promising aspects. However, there are still several limitations to be considered: First, the quality and consistency of the existing datasets may impact the performance of the model. Real-world data will be noisy and have missing values and sensor inconsistencies, where the model is best suited to obtaining a feature from the signals without this type of noisiness. Though it applies GNNs to the top effect modification mentioned above, such efficiency is yet to be applied in all those datasets or all signal modalities. The model generalizes well to different populations and sensor configurations. The datasets available may not represent all different types of people or conditions encountered in clinical settings, sports, or rehabilitation. These factors, therefore, could be tested further and improved upon the scalability and adaptability of the framework to other groups of people or sensor systems. Real-world application with the model might be challenging for variations in sensor types, configurations, and placements. Also, although the proposed framework addresses the issue of temporal dynamics and real-time monitoring, processing multi-modal signals may be too complex to prove suitable for real-time processing. Its implementation in a resource-constrained environment such as a wearable device will demand some optimization in the interest of efficiency without losing accuracy.

Finally, although it may be the case that great contributions are found in better health care, sport science, or rehabilitation, its translation into practice is very challenging. It needs collaboration with the industry partners to integrate GNN-based models in clinical practice and sports performance analysis, regulatory approval, and validation in real settings.

In summary, although the research targets a robust framework for multi-modal physiological signal decoding, its drawbacks in terms of data quality, model generalizability, and computational resources related to practical implementation should be addressed as part of future work.

6. Timeline Diagram

Phases	1-6 Months	7-12 Months	13-18 Months	19-24 Months	25-30 Months	31-36 Months
Phase I	Define Research Objectives and Questions Conduct a Comprehensive Literature Review Synthesize and Analyze Literature					
Phase II		Select Research Methodology Data Collection Initial Data Analysis and Method Refinement				
Phase III			Model Selection Model Training Model Evaluation			
Phase IV				Testing and Optimization		

				Integration		
Phase V					External Validation Results Analysis Manuscript Preparation	
Phase VI						Thesis writing and submission

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ANNEXURE – C

(On University Letterhead)

Directorate of Research & Development (DRD) where Research work will be carried out:(wherever applicable)

The Synopsis of Smt. HEENA is in order, approved and recommended by DRD and forwarded to Dean or Director of Faculty of Computer Science for consideration of registration for the degree of Doctor of Philosophy in the "**Decoding Physiological Signals with Graph Neural Networks**"

Place: JAIPUR **Signature with Seal of the Director, DRD**
Date: 11-03-2026

ANNEXURE – D

(On University Letterhead)

Dean/Director of Faculties

Recommendation of the Dean or Director, Faculty of COMPUTER SCIENCE

The Synopsis of Smt. HEENA is in order, approved and recommended by Director, DRD and forwarded to UREC/RAC for consideration of registration for the degree of Doctor of Philosophy in the "**Decoding Physiological Signals with Graph Neural Networks**"

Place: JAIPUR. **Signature with Seal of the Dean or Director of Faculty of COMPUTER SCIENCE**

Date: 11-03-2025

Place: JAIPUR
Date: 11-03-2025 **Signature with Seal of the President**

ANNEXURE – E

(On University Letterhead)

University Research Evaluation Committee (UREC) / Research Advisory Committee (RAC)

Recommendation of the Chairman, UREC/RAC Jayoti Vidyapeeth Women's University Jaipur

The Synopsis of Smt. **HEENA** is duly approved on the recommendation of for registration in the program Doctor of Philosophy in the "**Decoding Physiological Signals with Graph Neural Networks**"

Place: Jaipur **Signature with Seal of the Chairman, UREC/RAC**
Date: 11-03-2025

Registrar
Jayoti Vidyapeeth Women's University
Jaipur, Rajasthan